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Opportunistic data collection through delegation

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Abstract:

We consider a collection system where collectors move around gathering information generated by data producers. In such a system, data may remain uncollected when the number of collectors is insufficient to cover the whole population of producers. Motivated by the observation that node encounters are sufficient to build a connected relationship graph, we propose to take advantage of the inherent interactions among nodes and transform some producers into *delegates*. With such an approach, collectors only need to meet delegates that, in turn, are responsible for gathering data from a subset of standard producers. We achieve this goal through two contributions. First, we investigate several *delegation strategies* based on the relative importance of nodes in their social interactions (i.e., the node centrality). Second, by considering a *prediction* strategy that estimates the likelihood of two nodes meeting each other, we investigate how the delegation strategies perform on predicted traces. We evaluate the delegation strategies both in terms of coverage and size of the delegation existing real mobility data sets. We observe that delegation strategies that rely on localized information perform as well as the ones that consider a complete view of the topology.

Key-words: collaborative data collection; centrality; sparse networks; social interactions

Opportunistic data collection through delegation

Résumé : Nous considérons un système de collecte où les collectionneurs se déplacent et collectent les informations générées par les producteurs de données. Dans un tel système, les données peuvent ne pas être collectées lorsque le nombre de collectionneurs est insuffisant pour couvrir l'ensemble de la population des producteurs. Motivé par le fait que les rencontres de nIJud sont suffisantes pour construire un graphe connecté, nous proposons de profiter des interactions inhérentes entre les nIJud et transformer certains producteurs en *délégués*. Avec une telle approche, les collectionneurs ont seulement besoin de rencontrer les délégués que, à leur tour, sont responsables de la collecte de données d'un sous-ensemble des producteurs. Nous atteignons cet objectif grâce à deux contributions. Tout d'abord, nous étudions *plusieurs stratégies de délégation* basée sur l'importance relative des nIJud dans leurs interactions sociales (par exemple, la centralité du nIJud). Deuxièmement, en considérant une *stratégie de prédiction* qui donne les estimations de la probabilité d'une rencontre de deux nIJud, nous étudions les stratégies de délégation avec les traces prédit. Nous évaluons les stratégies de délégation à la fois en termes de couverture et de la taille du groupe de délégation en utilisant des traces de mobilité réelles. Nous n'observons que les stratégies de délégation qui se basent sur des informations localisées fournis aussi des bons résultats comparés aux résultats considérant une vue complète de la topologie.

Mots-clés : collecte collaborative de données, centralité, les réseaux de faible densité, les interactions sociales

1 Context and motivation

Cellular phones have recently been considered as a *pervasive mobile sensing platform* due to their increasing proliferation and multiple advanced capabilities (e.g., cameras, GPS, sensors, wireless communication). As a result, *global sensing* has appeared as one of the most challenging pervasive applications aiming at improving the quality of life of the population [21]. In such applications, also referred to as participatory sensing, mobile nodes (or *producers*) generate data from observations of the surrounding environment or from users (healthy, activity, behavior, etc) and send it to a central entity that evaluates the global behavior of the system from localized views. In addition, the underlying wireless network may face problems of intermittent and/or sparse connectivity, high degree of mobility, and unreliable links, which greatly impairs the effectiveness of both data collection and delivery.

There are many possibilities of how sensed data can be sent to the central entity. When possible, the most straightforward one is to rely on a reliable deployed infrastructure that maintains permanent connectivity with each one of the nodes, e.g., the 3G network. Nevertheless, there are many situations where the use of such infrastructure is prohibitive, either because of cost constraints or capacity limitations. Indeed, depending on the target scenario, information generated by each node might be huge, requiring a significant amount of communication resources to transfer sensed data to the infrastructure (e.g., multimedia contents).

We propose to design a collection system composed of specialized devices called *collectors* whose role is to move around and collect data when they enter within communication range with producers. As part of a general-interest system, collectors can be provided by administrative entities in order to alleviate end-users from using a costly deployed infrastructure (e.g. 3G access). Our idea is to use direct communications among nodes whenever available and use that infrastructure as little as possible. There are two main issues that arise when designing such a system: (i) the number of producers might be much larger than the number of collectors and (ii) we need to decide which collector to “visit” which producer, a challenging problem considering the previous issue. To address these challenges, we need alternative solutions to overcome the insufficiency of the collection system. We suggest to benefit from the inherent contact opportunities that emerge due to the natural mobility of the nodes to tackle these problems.

To the best of our knowledge, this is the first time that this specific problem is addressed. Indeed, although previous work makes use of mobile entities to perform some network task, the perspective therein is different from ours [11, 14, 25]. In particular, data mules and message ferries are mobility-assisted strategies that aim at providing “connectivity opportunities” among nodes [14, 25]. These approaches are concerned with controlling the trajectories of ferries or mules to meet static or mobile nodes with the goal of minimizing message drops. Trajectories are adjusted based on requests from nodes, or the nodes adjust themselves their trajectories to meet the ferries. These approaches only partially solve the problem considered in this paper. Indeed, we do not deal with collectors placement or their trajectory design to visit all producers in the network. We instead focus on detecting *which* subset of producers could help collectors in the data collection task, while keeping their “normal” behavior within the network.

More specifically, we propose to take advantage of the inherent mobility of producers and transform some of them into *delegates* of the collection system. Delegates are responsible to collect data from other producers and serve as intermediate relays between them and the collectors (see Fig. 1). This is motivated by the fact that social

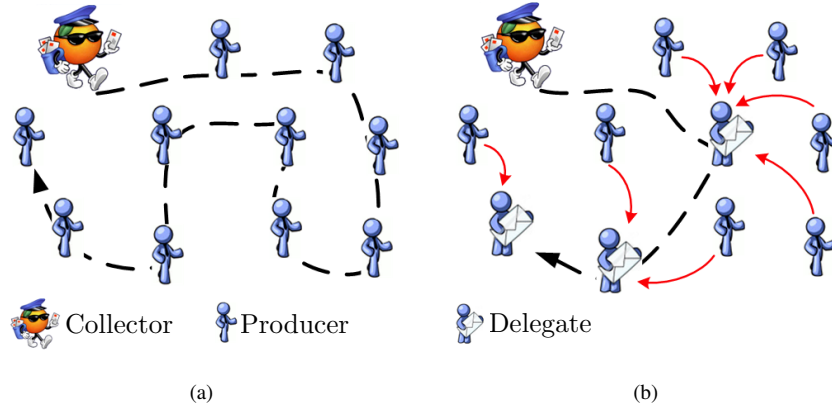


Figure 1: (a) The collector has to visit all producers. (b) Delegates gather information on behalf of the collector.

networks exhibit the small world phenomenon which comes from the observation that individuals are often linked by a short chain of acquaintances [20] and that encounters are sufficient to build a connected relationship graph [12]. The problem here is to determine which producers should be promoted as delegates. To this end, we make the following contributions:

- Because contacts are not deterministic, we propose a *prediction* strategy to estimate the likelihood of two producers meeting each other (Section 3).
- Based on such a prediction system, we investigate different social-inspired strategies to select which producers should become delegates (Section 4).
- We evaluate the strategies using trace-driven analysis obtained in real situations (Section 5).

In all of the social-based strategies, the selection of delegates is based on the quantification of the relative importance of a producer in the network. We investigate two types of centrality approaches, namely degree and betweenness, combined with different network knowledge, namely global and ego networks (see Section 4). The analysis are performed on two different data sets available in the literature (Dartmouth College wireless traces [16] and San Francisco taxi traces [24]). By using measured and predicted traces generated from these data sets (see Section 3), we investigate the properties of the social-based strategies in terms of coverage and size of the resulting delegation set. We make then recommendations for the use of specific social-based strategies and show that the use of predicted traces is effective for the selection of good delegates (see Section 5). Finally, we discuss related works and present our work outlook at the end of this paper (see Section 6 and Section 7).

2 Problem definition and sketch of the solution

2.1 What do we do?

As briefly defined in the introduction, our goal is to select a subset of *producers* that will be promoted as *delegates* to help the *collectors* obtain the data generated by each producer. In fact, producers that are promoted as delegates do not have to change their trajectories to meet collectors or other producers. They continue producing their own data while gathering data from producers they meet. In the rest of this paper, the words *node* and *producer* will be used interchangeably.

Because of storage and communication capacity constraints, we wish to avoid relying on fully epidemic approaches. We adopt in this paper a two-level strategy where a node is either a delegate or a producer that meets a delegate. In this way, simple producers transfer their data to one or more delegates they meet and collectors have only to visit these latter. Note that no forwarding is required, since data is transmitted through direct contact opportunities. Furthermore, in order to save deployment costs, it is also desirable that the number of delegates be as small as possible, so that fewer collectors are necessary (i.e., less nodes to visit). In particular, let $\Pi = \{p_1, p_2, \dots, p_P\}$ be the set of producers in the network. Our problem consists then in computing the delegates subset Δ of Π such that Π is the smallest subset of producers whose movement guarantees the biggest achievable number of visited other producers within a certain time slot. Finally, we allow the utilization of an already deployed infrastructure (e.g., 3G network) but only for control information, i.e., to help the operation of the system (see Section 3).

2.2 How do we do?

In order for the system to compute the set Δ of delegates, we need to know in advance what will be the contact patterns among producers. We have two alternatives to solve this problem. Either we promote all producers as delegates, which would bring our system to the original problem (i.e., the collectors visit all producers), or we try to predict future encounters. We naturally adopt the latter alternative (Section 3). Once encounters are predicted, we apply *social-inspired selection schemes* consisting in the quantification of the relative importance of producers, to compute the set of delegates (see Section 4).

Globally speaking, the system works as follows (to be detailed in the following sections):

- In the very beginning, there is no way to do predictions in the network (i.e., no history available). Collectors must then visit all producers.
- As the network operates, nodes store their encounters during some time (we refer to this as *measurement period*). At the end of this period, nodes send their contact patterns to a centralized administrative entity using an already deployed network infrastructure (e.g., 3G).
- The centralized administrative entity uses the contact patterns to predict future encounters. Based on this prediction, the set of delegates is determined. The producers selected as delegates are informed through the 3G infrastructure that they will have to play this role during the next measurement period. The collectors are also informed about the set of delegates to be visited.

- Since delegates are computed based on predictions, it is likely that some producers will be not covered by any delegate. In this case, these “isolated” producers are the only nodes to use the deployed infrastructure to upload their data. In this way, we limit the use of the 3G networks for data collection, reducing cost constraints and avoiding the capacity limitation problem.

2.3 What do we not do?

Our focus here is on the study of social interaction of producers for delegates selection. Trajectory design of collectors in terms of time and space for guaranteeing delegates visits is not considered in this paper, although we leave this for future work. As discussed in Section 3, we use simple prediction algorithms, allowing quick computation and short measurement periods. In this paper, such algorithms are sufficient for the validation of the proposed strategies. More sophisticated algorithms could be used, which would allow decreasing the number of not covered producers due to wrong predictions. This is also left for future work.

3 Sketch of the solution

In this section, we present a high-level view of our approach. By applying different social-inspired strategies, we investigate the relative importance of producers in their social interactions or in the global network and select a set of potential good relay nodes (i.e., delegates) to help collectors perform their task. In this scheme, data is first collected from producers by delegates and then sent by these latter to the collectors.

There are many ways to predict future contacts based on the history of encounters [8, 18]. In this paper, we propose to use a slotted prediction strategy with a history window of two days (see explanation below). We will see in Section 5 that, although simple, this strategy leads to good results.

Let $C(i)$ be the *collection period* i of duration $|C|$. We divide this period into J slots of fixed duration so that $C(i) = \{c(i, 1), c(i, 2), \dots, c(i, J)\}$. To each $c(i, j)$ we associate two matrixes $M(i, j) = [N \times N]$ and $P(i, j) = [N \times N]$, where N is the total number of producers.

The first matrix $M(i, j)$ is called the *measurement matrix*. In this matrix, element $m_{x,y}(i, j)$ is 1 if node x meets node y at least once during the time slot $c(i, j)$, and 0 otherwise. As stated before, the problem is that we cannot compute the delegates based on the measurement matrix for a given time slot because this matrix is only available at the end of the slot period (after the real contacts are observed).

The second matrix $P(i, j)$ is the *prediction matrix*. Each element of this matrix is based on the history of observations previously made. We propose to rely on the observations made during the same slot of the previous collection periods. We predict that a contact will happen if it already happened during the same slot of the previous two measurement periods. This procedure is illustrated in Fig. 2. The reason for this value is that we empirically observed that this leads to better results. More formally, we have:

$$p_{x,y}(i, j) = \begin{cases} 1, & \text{if } [m_{x,y}(i-1, j) \wedge m_{x,y}(i-2, j)] = 1, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

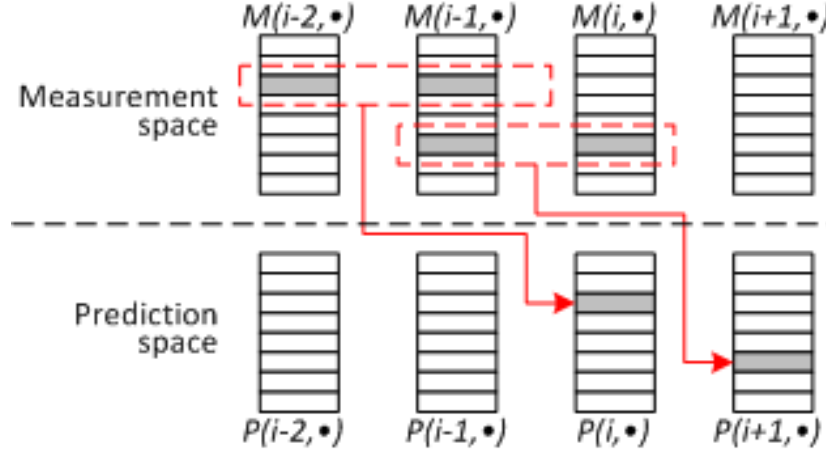


Figure 2: Observed encounters are used to feed the prediction matrix.

4 Social-oriented delegation

In the previous section, we proposed a prediction approach to determine the encounters that are likely to happen during a given time slot. We have now to determine, based on these expected encounters, which producers should be promoted to delegates. In the following, we investigate several strategies to this end. We classify them based both on the social metric and on the awareness a producer has about the topology.

4.1 Social-inspired metrics

To investigate the relative importance of producers, we exploit the well known centrality concept from graph theory and network analysis. Centrality will allow us designing how important a producer is within a social sphere, in order to identify potential delegates. In a social network, an individual is considered as important if, for instance, she/he has a strong capability of meeting others or connecting disjoint tightly connected groups. In the literature, “importance” is described through three different metrics [9, 10]: closeness, degree, or betweenness. We use the last two centrality metrics in our analysis and a combination between them, described hereafter.

Degree centrality (DC). This metric describes the number of direct connections that involve a given node. In this way, a node with high degree centrality can be seen as a popular node. This also means it can be used as a good conduit for information exchange, since it maintains contact with numerous other network nodes. Thus, by exploiting degree centrality we aim to see if node degree can be used to find a near to perfect level of coverage, without having to select large numbers of nodes. The degree centrality of a given producer p_i is calculated by simply counting the number of contacts this producer has during a time slot with other producers in the network: $D(p_i) = |\mathbf{N}_{p_i}|$.

Betweenness centrality (BC). This metric measures the frequency a node lies on the paths linking other nodes. In this way, a node with a high betweenness centrality is on more paths than the average and, therefore, has the capacity to facilitate interaction

between the nodes that it links. The betweenness of producers is thus computed by analyzing all the paths between all nodes in the network, and then scoring a producer based on the amount of times it appears on the paths of other nodes. Note, however, that, nodes with high betweenness do not frequently have a large number of connections, since they are usually the only route to a place and are frequently “bridging nodes”. By harvesting these nodes, we attempt to see if they are enough to cover the rest of the network.

Betweenness and degree centrality (BDC). By combining popularity and betweenness, we hope to play off the strengths of both of these metrics, whilst overcoming their shortcomings. A metric utilizing both degree and betweenness centrality seeks to gain the benefit of connecting to a large number of nodes, whilst simultaneously reaping the benefit of selecting nodes that bridge groups of nodes within the network. This would then ensure capturing nodes that bridge distinct cliques of nodes as well as network locations that would expect to see the most traffic. Considering we are interested in determining a subset of size $|\Delta|$ of good delegates, the resulting set BDC is half made up of top nodes in the betweenness centrality set BC, and half made up of high popular nodes in the degree centrality set DC.

4.2 Topology-awareness

We compute the three metrics presented above to each node by considering nodes have access to the following levels of network knowledge:

Complete and bounded network (C). Also referred to as socio-centric network, it requires the complete knowledge of the network topology. A large node population may thus make difficult the analysis of centrality metrics in this kind of network topology. Nevertheless, we use this socio-centric network to get the upper-bounded results to be compared to the ones obtained when using knowledge-limited network topologies.

Ego-centric networks (E). This network topology represents the network viewed from the perspective of a single node and can be locally computed without the complete knowledge of the entire network. An ego-centric network consists of a single actor (named *ego*), its 1-hop neighbor (named *alters*), and all the links among those alters. This means the ego node itself can work out its ego network, after exchanging its neighborhood list with each new encounter, which allows distributing computation. An Ego network requires less state than a 2-hop neighborhood topology such as the one required for the computation of dominating sets. It has been shown in the literature that degree and betweenness centrality, when computed in ego networks, allow quite good results when compared to the socio-centric networks [19].

We combine the previous described centrality metrics and types of networks and originate six strategies, which we investigate in the rest of this paper.

4.3 Benchmark strategy

For the sake of comparison, we also consider a benchmark solution that leads to the best possible result. More specifically, the ideal case would be the smallest set of delegates that guarantee 100% coverage (i.e., during the collection period, all producers could deliver their data to either a collector or a delegate). This corresponds to computing the minimum dominating set (MDS) on the encounter graph for each time slot. Because

Table 1: Acronyms for the different strategies.

<i>Acronym</i>	<i>Strategy</i>
DC-C	Degree centrality with complete view
DC-E	Degree centrality with egocentric view
BC-C	Betweenness centrality with complete view
BC-E	Betweenness centrality with egocentric view
BDC-C	Betw. and degr. centrality with complete view
BDC-E	Betw. and degr. centrality with egocentric view
Benchmark	Dominating set

this problem is known to be NP-hard, we consider an alternative solution borrowed from the computation of multi-point relays as our benchmark [1].

A dominating set DS of a graph $G = (V, E)$ is a subset $V' \subseteq V$ such that every vertex not in V' (i.e. for all $u \in V - V'$) is adjacent to at least one vertex of V' by some edge (i.e., there is a $v \in V'$ for which $(u, v) \in E$). We have used the following greedy algorithm for computing dominating sets, which takes $O(m^2)$ time for a maximum connectivity degree m [1]: (i) begin with an empty set; (ii) select the nodes that are the only ones neighbor of some two-hop neighbors of i , and add them to the DS set; (iii) add in the DS the neighbor node of i that covers the largest number of two-hop neighbors of i that are not yet covered by the current DS . Repeat this step until all two-hop neighbors are covered.

The results obtained with the proposed delegation strategies are then compared to the benchmark. Note that, unlike [22], connection among delegates is not required here, since collectors will later visit them. The reason for not adopting the benchmark as the delegation strategy is that, as we will see in Section 5, although leading to better coverage, it requires a large number of delegates to perform the work.

For the sake of clarity, we present in Table 1 the acronyms used in the remainder on this paper.

5 Evaluation

We evaluate the performance of the social-inspired delegation strategies described in Section 4 using measured and predicted traces out of two data sets. We first describe the data sets used and the evaluation methodology in Sections 5.1 and 5.2, respectively. Secondly, in Section 5.3, we investigate the performance of the benchmark approach when applied to the different traces. Thirdly, by considering nodes with different network topology awareness (cf., Section 4), we evaluate the performance obtained with each social metric (cf. Section 5.4). Finally, we provide some discussion on the results in Section 5.5.

5.1 Data sets and methodology

We decided to use two data sets that are well-known by the research community: Dartmouth College campus and San Francisco Taxi cabs. By nature, they show different mobility patterns, types of users, and environment conditions. We expect then to observe different social behaviors, resulting in different usage models. This diversity will allow us better understanding the characteristics of the analyzed strategies. Although well-known, we briefly describe them in the following.

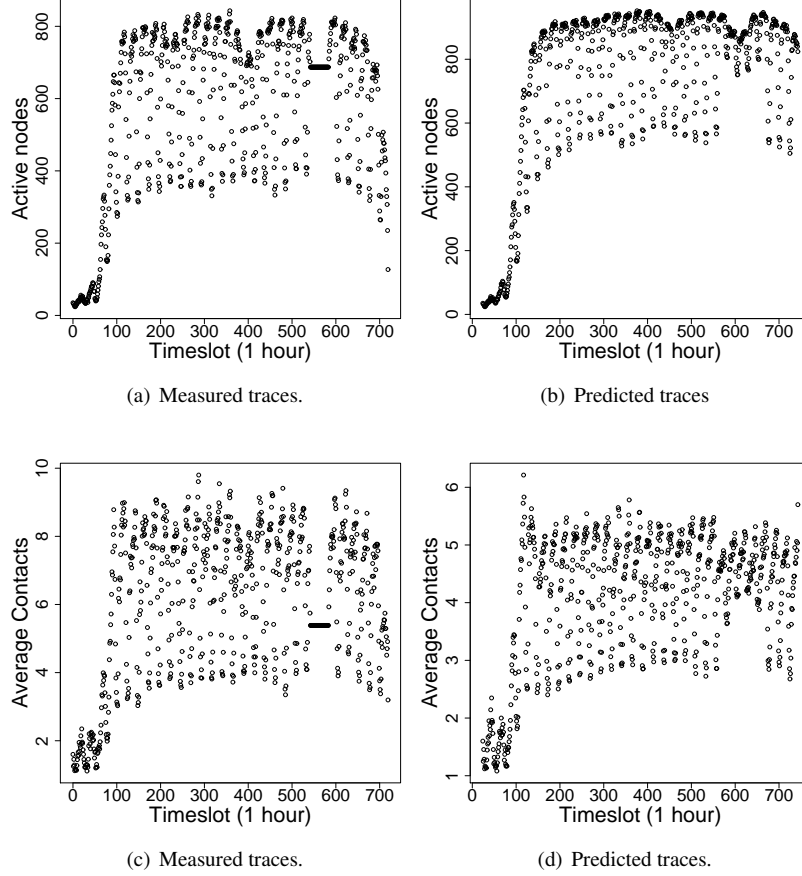


Figure 3: Dartmouth measured and predicted traces: (a)-(b) active nodes and (c)-(d) average number of contacts over 695 hours, using time slots of 1 hour.

Dartmouth College campus [16]. This data set shows associations and disassociations of wireless devices with 566 wireless access points in the Dartmouth College campus. For the purposes of this work, this data set has to be translated into a contact graph. In the literature, authors generally assume that two nodes are in contact with each other if they are associated with the same access point at the same time [5]. We decided instead to use the geographic coordinates of the nodes and consider that two nodes are in contact if their distance is below 250 meters. To obtain their geographic positions, we adopt the filtering approach proposed by Kim et al. [15]. We consider mobility information over one month and focus our analysis on the 1,000 most active nodes (in terms of presence). Note that nodes are not active at the same time, leading to an average number of 577 active nodes and 6 contacts per node per time slot of one hour, as shown in Figs. 3(a) and 3(c). The corresponding *predicted traces*, generated following the prediction strategy described in Section 3, lead to an average number of 737 active nodes and 4 contacts per node, as shown in Figs. 3(b) and 3(d).

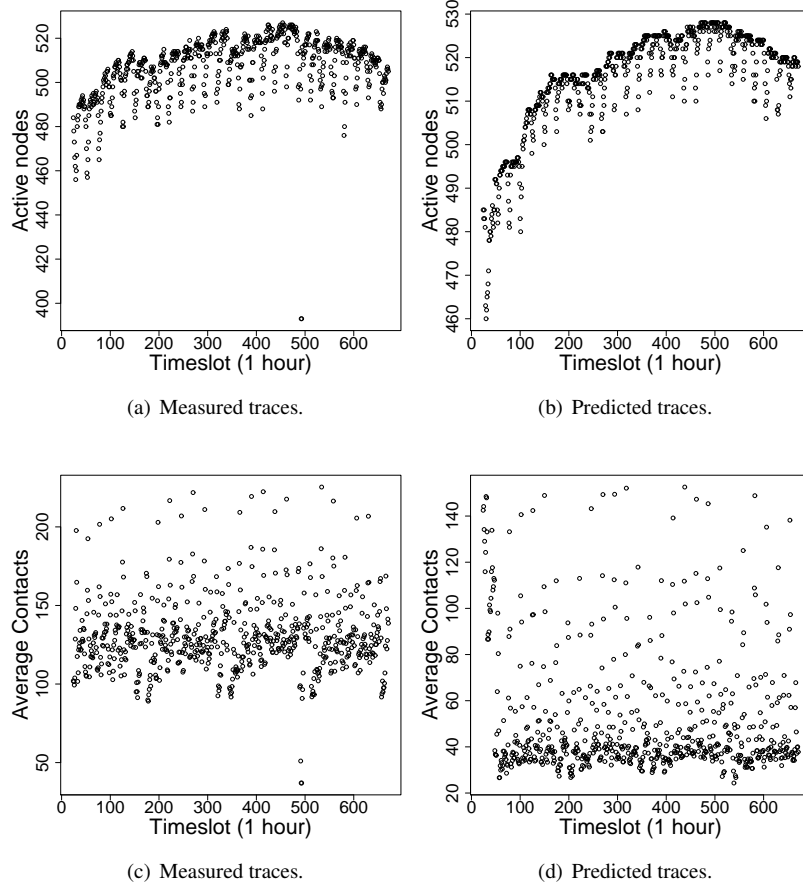


Figure 4: Taxi measured and predicted traces: (a)-(b) active nodes and (c)-(d) average number of contacts over 672 hours, using time slots of 1 hour.

Taxi cabs in San Francisco [24]. This data set describes the movement of taxicabs in San Francisco. GPS devices installed in the cabs are polled every minute or so whether they are free, inactive, or on route. We consider movements of the entire population of taxicabs that were active during a period of 28 days, resulting in a total of 542 nodes. We have, per time slot, an average number of 506 active nodes and of 130 contacts per node, as shown in Figs. 4(a) and 4(c). As in the Dartmouth trace, we consider that two taxis are in contact if their distance is below 250 meters. The predicted results are shown in Figs. 4(b) and 4(d), with an average number of 515 active nodes and 52 contacts per node.

Prediction vs. measurement. Note that for both data sets, the predicted traces resulted in lower average numbers of contacts per node and higher average numbers of active nodes. The reasons are as follows. On the one hand, we predict that a contact will happen at a given time slot if the same contact happened in the equivalent slot in *both* the two previous days. This explains why the expected degree is lower. On the other

Table 2: Avg. results for the benchmark.

Data set	Traces	$ \Delta $	% delegates
Dartmouth	measured	304.36	56.14
	predicted	508.43	70.97
Taxi	measured	326.06	64.22
	predicted	419.33	81.38

hand, we assume the a node will be active in a given time slot if it was active in *either* of the two previous days. This results in a higher expectation.

5.2 Evaluation methodology

We are interested in selecting a limited set of producers Δ as delegates to opportunistically collect data generated by producers. In order to evaluate the performance of each delegation strategy, we focus on both coverage and size of the resulting Δ sets, on a per-slot basis. We evaluate the coverage property of the strategies by determining the percentage of producers not met by any of the delegates – we refer to this parameter as *missed nodes*. We also evaluate the size of the $|\Delta|$ set as an indicator of the efficiency of the delegation system.

5.3 Benchmark analysis

We first evaluate the performance of the benchmark approach when applied to the measured traces and the corresponding predicted traces, of both Dartmouth and Taxi data sets. Table 2 summarizes the average amount of producers that become delegates (in both absolute and relative terms). As previously discussed, we observe that the sizes of the prediction sets are larger than the measured ones (cf., Section 5.1).

In order to evaluate the precision of results obtained with the predicted traces, we investigate (i) the delegates that appear in both measured and predicted traces and (ii) the amount of nodes not covered when we use the predicted delegates. Fig. 5(a) (resp. Fig. 5(b)) shows the overlap comparison for the Dartmouth data set (resp. Taxi data set). An average of 71.47% (resp. 86.57% in the Taxi data set) of delegates found using the measured traces are also present in the corresponding predicted sets. Additionally, Fig. 5(c) shows for the Dartmouth data set (resp. Fig. 5(d) for the Taxi data set) that an average of 5.7% (resp. 0.08%) of nodes are not covered by the predicted delegates. These results are encouraging and confirm that the prediction scheme leads to good performance.

5.4 Topology-awareness

We investigate now the performance of the social-inspired metrics for delegate selection according to the topology-awareness of nodes. For every strategy discussed hereafter, we provide: (i) tables summarizing the average percentage of set sizes, for both the measured and predicted traces, (ii) figures showing the overlap between the measured and predicted delegate sets, and (iii) figures showing the amount of uncovered producers if we use the predicted delegates.

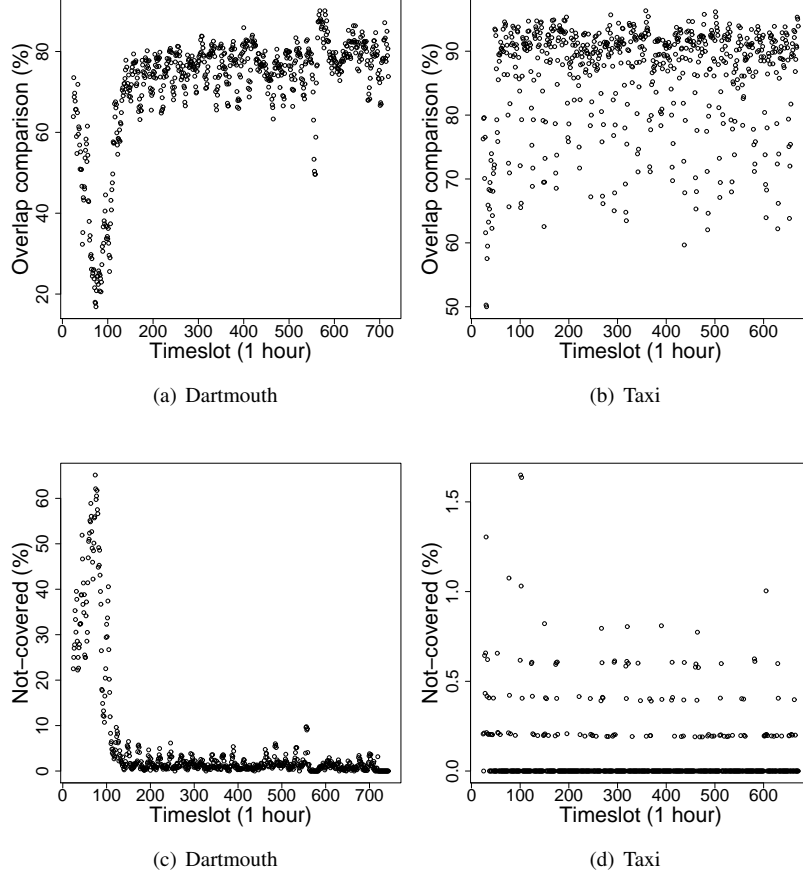


Figure 5: Benchmark approach. (a)-(b) Percent of nodes per timeslot in the Δ set obtained from the measured traces that are also found in the Δ sets obtained from the predicted traces: (a) Dartmouth: 71.47%, (b) Taxi: 86.57%. (c)-(d) Amount of not-covered nodes by the Δ sets gotten from the predicted traces: (c) Dartmouth: 5.7% (d) Taxi: 0.08%.

5.4.1 Influence of complete network view (C)

We consider here that nodes have a complete view of the network at each time slot. Producers are first ordered based on their social influence. In order to select the best delegates, we use as reference the same size of the delegate set obtained for the measured data set in the benchmark approach, and pick the top-rated producers until the delegate sets' sizes are the same.

DC-C. Table 3 summarizes the average percentage of missed nodes and the set size resulting from the degree centrality selection applied to the complete network. Fig. 6(a) shows that an average of 71.42% (resp. 86.77% in Fig. 6(b)) of delegates overlapping between the traces, while Fig. 6(c) shows that an average of 9.22% (resp. 0.59% in Fig. 6(d)) of nodes are not be covered predicted delegates.

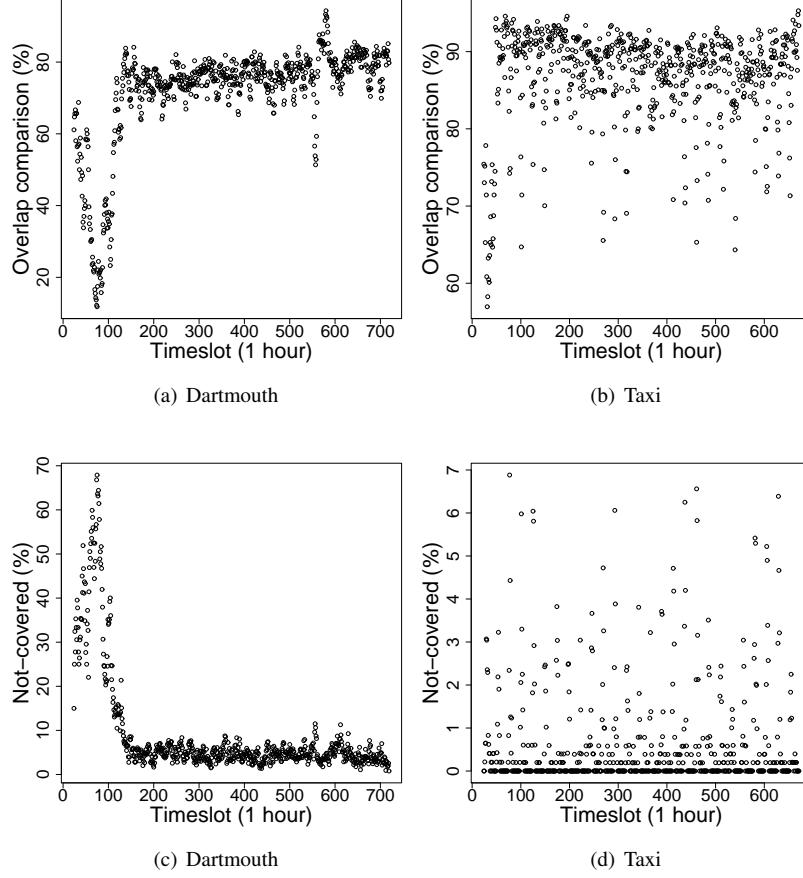


Figure 6: DC-C strategy. (a)-(b) Percent of nodes per timeslot in the Δ set obtained from the measured traces that are also found in the Δ sets obtained from the predicted traces: (a) Dartmouth: 71.42% (b) Taxi: 86.77% . (c)-(d) Amount of not-covered nodes by the Δ sets gotten from the predicted traces: (c) Dartmouth: 9.22% (d) Taxi: 0.59%.

Table 3: Avg. results for DC-C.

Data set	Traces	$ \Delta $	% delegates
Dartmouth	measured	304.36	55.08
	predicted	508.43	70.87
Taxi	measured	325.09	64.02
	predicted	418.59	81.24

BC-C. As with the previous strategy, Table 4 shows the results of the betweenness centrality selection applied to the complete network. Fig. 7(a) shows that an average of 86.76% (resp. 99.07% in the Taxi data set in Fig. 7(b)) of delegates' overlap. Fig. 7(c) shows that an average of 7.31% (resp. 0.13% in the Taxi data set) of nodes remain uncovered.

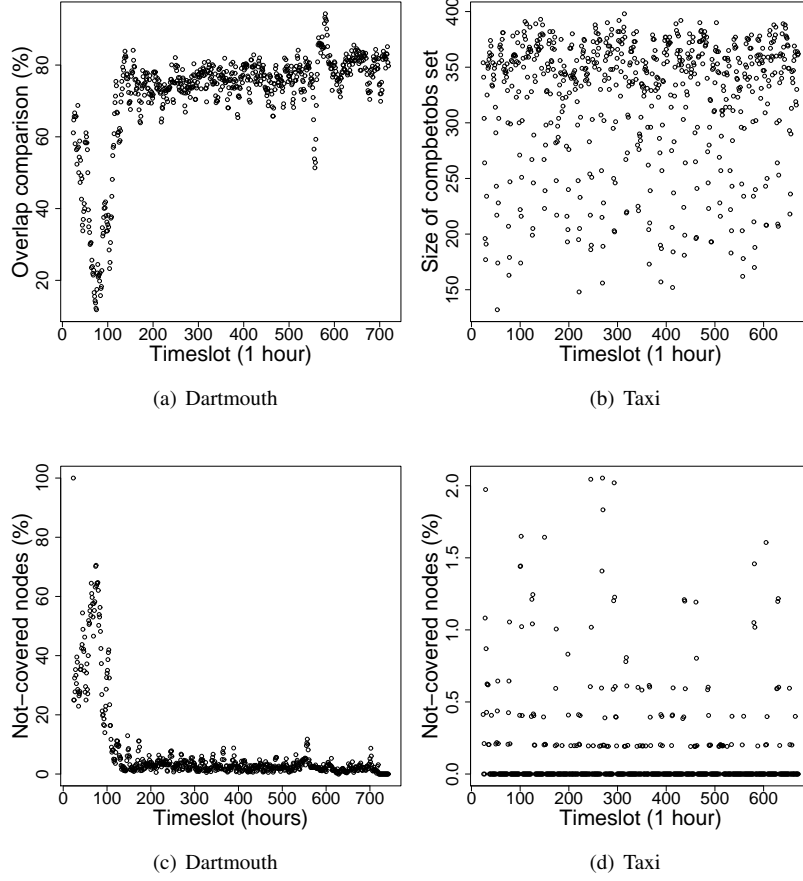


Figure 7: BC-C strategy. (a)-(b) Percent of nodes per timeslot in the Δ set obtained from the measured traces that are also found in the Δ sets obtained from the predicted traces: (a) Dartmouth: 86.76%, (b) Taxi: 99.07%. (c)-(d) Amount of not-covered nodes by the Δ sets gotten from the predicted traces: (c) Dartmouth: 7.31% (d) Taxi: 0.13%.

Table 4: Avg. results for BC-C.

Data set	Traces	$ \Delta $	% delegates
Dartmouth	measured	304.30	56.12
	predicted	507.54	70.97
Taxi	measured	326.06	64.22
	predicted	419.33	81.38

BDC-C. Table 5 summarizes the results for the BDC-C strategy. As in the previous two cases, we show in Figs. 8(a) and 8(b) the overlaps between the measured and predicted traces for both data sets. We observe an average overlap of 74.86% for the Dartmouth data set and 90.64% for the Taxi data set. Figs. 8(c) and 8(d) show that the proportion of nodes not covered is 8.04% in the Dartmouth case and 0.23% in the Taxi case.

Table 5: Avg. results for BDC-C.

Data set	Traces	$ \Delta $	% delegates
Dartmouth	measured	304.36	56.14
	predicted	507.33	70.87
Taxi	measured	326.06	64.22
	predicted	419.33	81.38

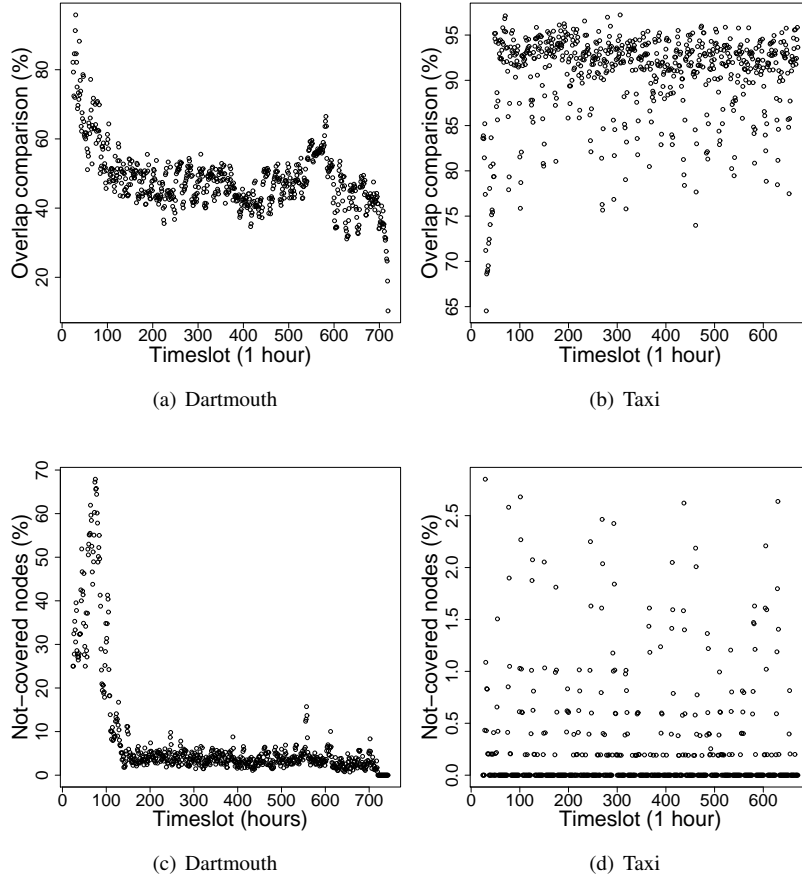


Figure 8: BDC-C strategy. (a)-(b) Percent of nodes per timeslot in the Δ set obtained from the measured traces that are also found in the Δ sets obtained from the predicted traces: (a) Dartmouth: 74.86%, (b) Taxi: 90.64%. (c)-(d) Amount of not-covered nodes by the Δ sets gotten from the predicted traces: (c) Dartmouth: 8.04% (d) Taxi: 0.23%.

5.4.2 Influence of ego-centric network view (E)

Nodes are now considered to have an ego-centric view of the network. The goal is to verify if nodes can locally select good delegate sets. As in the previous section, the sizes $|\Delta|$ of the measured sets in the benchmark case are used as reference sizes for the delegate sets. The difference here is that producers use the ego-centric view instead of

Table 6: Avg. results for DC-E.

Data set	Traces	$ \Delta $	% delegates
Dartmouth	measured	159.62	32.6
	predicted	255.22	38.9
Taxi	measured	33.15	6.57
	predicted	84.93	16.48

Table 7: Avg. results for BC-E.

Data set	Traces	$ \Delta $	% delegates
Dartmouth	measured	110.06	21.78
	predicted	190.88	28.34
Taxi	measured	31.67	6.27
	predicted	80.58	15.64

Table 8: Avg. results for BDC-E.

Data set	Traces	$ \Delta $	% delegates
Dartmouth	measured	174.75	35.29
	predicted	292.54	44.02
Taxi	measured	37.71	7.48
	predicted	97.93	19.01

the complete view of the network, which gives a different network view to each node. Thus, each node firstly ranks all the nodes it sees in its ego-centric network according to the considered social-inspired strategy. An ordered list containing the best nodes of each ego network is then generated and the best $|\Delta|$ nodes are selected to compose the delegate sets. Since duplications can happen (i.e. a best node in the ego network of node p_i can also be the best node in the ego network of node p_j), they are removed from the final selected delegate set. This may result in smaller sets compared to the ones provided by the benchmark approach.

DC-E. Table 6 summarizes the average percentage set sizes resulted from the degree centrality selection applied to an ego-centric network. Details are presented in Fig. 9(a), which shows that an average of 61.94% (resp. 71.68% in the Taxi data set in Fig. 9(b)) of delegates overlap between the traces. Fig. 9(c) shows that an average of 11.85% of nodes (resp. 1.88% in the Taxi data set in Fig. 9(d)) remain uncovered.

BC-E. We now evaluate the betweenness centrality selection applied to an ego-centric network. The results are summarized in Table 7. Fig. 10(a) shows an delegate overlap of 69.78% on average (resp. 77.63% in the Taxi data set in Fig. 10(b)), while numbers of uncovered producers are presented in Figs. 10(c) and 10(d). The average values are 15.7% for the Dartmouth trace and 1.91% for the Taxi data set.

BDC-E. Table 8 summarizes the results for the BDC-C strategy. Fig. 11(a) shows that, on average, 69.24% (resp. 73.33% in the Taxi data set) of the delegates overlap between the traces. In terms of producers that remain uncovered, Fig. 11(c) details the results for the Dartmouth set, with an average of 10.67%, while Fig. 11(d) shows 1.48% of producers left uncovered in the Taxi data set.

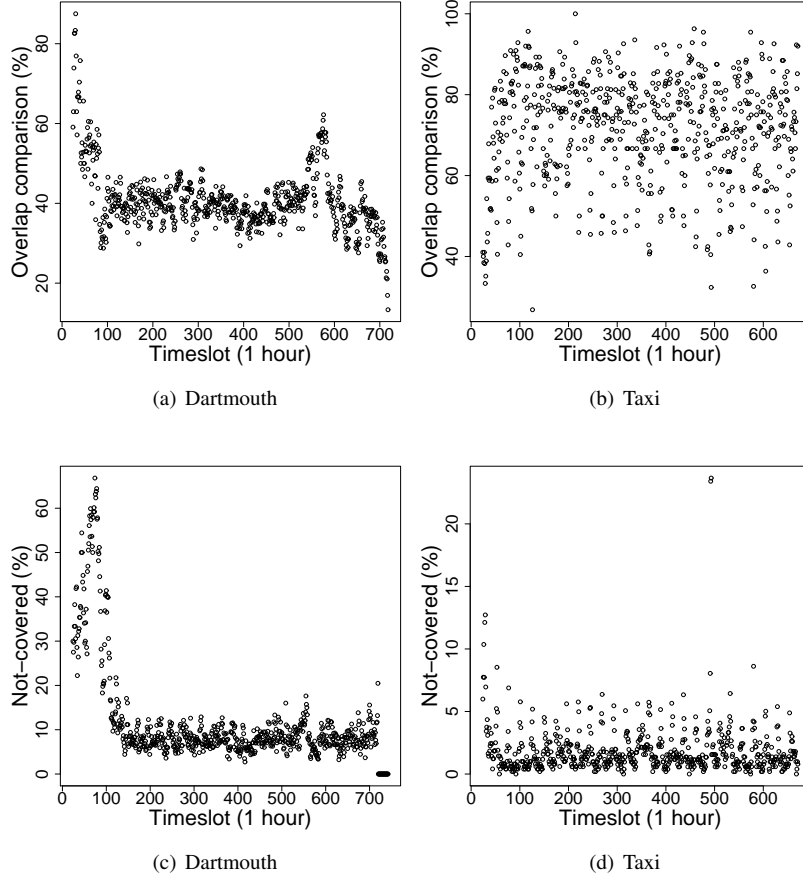


Figure 9: DC-E strategy. (a)-(b) Percent of nodes per timeslot in the Δ set obtained from the measured traces that are also found in the Δ sets obtained from the predicted traces: 11.85% (d) Taxi: 1.88%.

Table 9: Summary of Dartmouth results.

Strategy	% missed	% delegates
Benchmark	5.7	70.97
DC-C	9.22	70.87
BC-C	7.31	70.97
BDC-C	8.04	70.87
DC-E	11.85	38.9
BC-E	15.7	28.34
BDC-E	10.67	44.02

5.5 Discussion

To summarize our analysis, we present in Tables 9 and 10 the average percentage of producers selected as delegates, from the predicted sets and the average percentage of missed producers in the measured traces when those delegates are used. Although

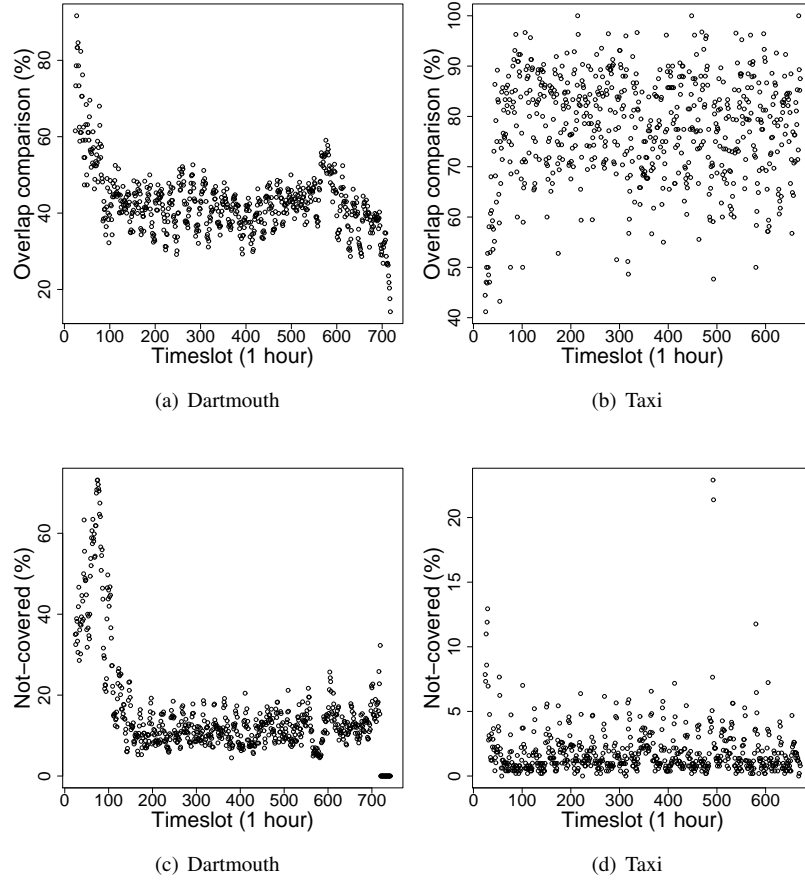


Figure 10: BC-E strategy. (a)-(b) Percent of nodes per timeslot in the Δ set obtained from the measured traces that are also found in the Δ sets obtained from the predicted traces: (a) Dartmouth: 69.78%, (b) Taxi: 77.63%. (c)-(d) Amount of not-covered nodes by the Δ sets gotten from the predicted traces: (c) Dartmouth: 15.7% (d) Taxi: 1.91%.

Table 10: Summary of Taxi results.

Strategy	% missed	% delegates
Benchmark	0.08	81.38
DC-C	0.59	81.24
BC-C	0.13	81.38
BDC-C	0.23	81.38
DC-E	1.88	16.48
BC-E	1.91	15.64
BDC-E	1.48	19.01

we know that degree and betweenness measures on both ego-centric and complete networks are equivalent [19], we still were surprised to see that, in both data sets and for

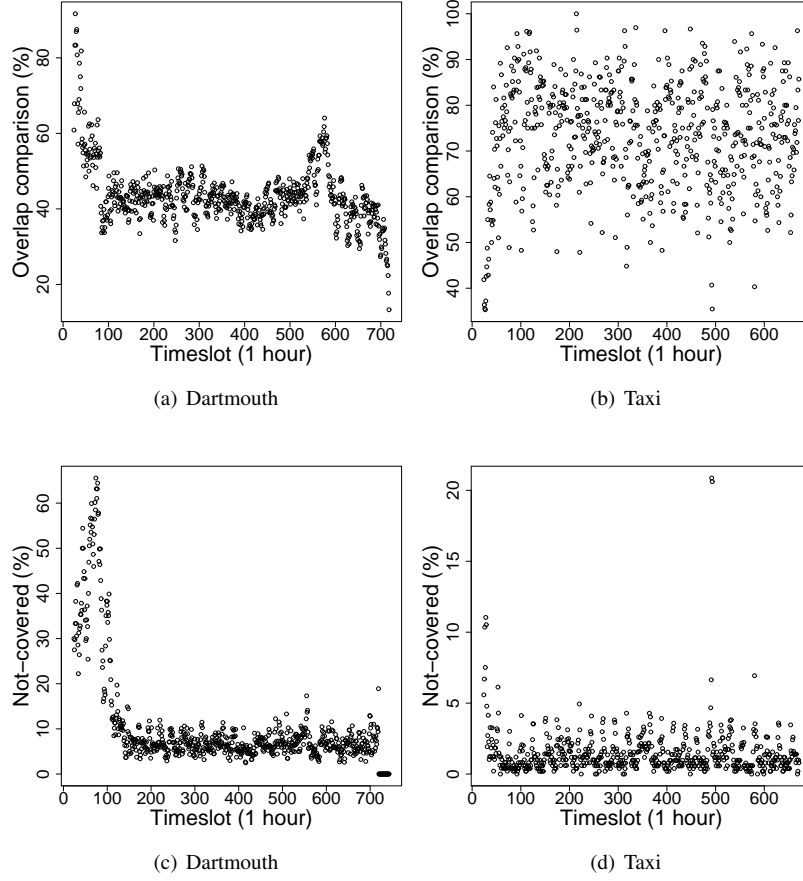


Figure 11: BDC-E strategy. (a)-(b) Percent of nodes per timeslot in the Δ set obtained from the measured traces that are also found in the Δ sets obtained from the predicted traces: (a) Dartmouth: 69.24%, (b) Taxi: 73.33%. (c)-(d) Amount of not-covered nodes by the Δ sets gotten from the predicted traces: (c) Dartmouth: 10.67% (d) Taxi: 1.48%.

equivalent coverage, ego-centric solutions require a much smaller number of delegates. Additionally, we observe that better coverage and set sizes are obtained for the Taxi data set. This is expected because of its much higher average contacts per nodes (cf. Fig. 4).

For the sake of clarity, we show in Fig. 12 the average percentage of delegates against the average percentage of uncovered producers, as described in Section 5.4. We can observe that the results obtained through prediction are equivalent to the ones obtained through measurements. This confirms our expectation that: (i) a window of two days is enough to obtain good prediction and (ii) our prediction strategy is a reliable basis for good delegate set selection.

We have also investigated times slots of 24 hours, which resulted, as expected, in smaller delegate sets (we do not show the results here due to the lack of space. It is

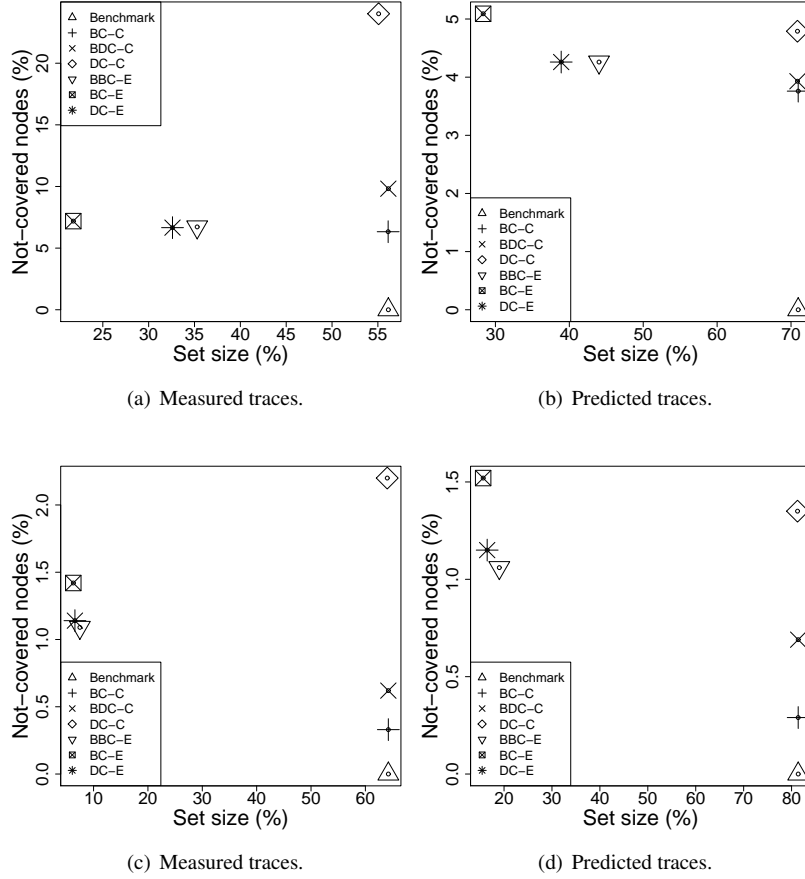


Figure 12: Average percentage of delegates as a function of the average percentage of not-covered nodes. (a)-(b) Dartmouth data sets. (c)-(d) Taxi data sets.

worth noting however that the time slot impacts the speed and trajectory design of the collectors. As for the design of collectors' trajectories, this impact study is left for future work.

6 Related work

Reactive and proactive schemes have been proposed in the domain of data delivery in sparsely connected networks and mobility-assisted schemes. Reactive schemes rely on movement that is inherent of the devices themselves to help deliver messages. When disconnected, nodes passively wait for their own mobility to allow them to reconnect [3, 17, 23]. More closely related to our work, proactive approaches make nodes modifying their trajectories for communication purposes, making use of mobility to

improve capacity and connectivity [2, 14, 25]. In particular, data mules [14] and message ferrying [25] are mobile nodes that move around the deployment area and take responsibility for carrying data between nodes. Smart-Tag [2] proposes to use mobile individuals to carry messages between disconnected devices and physical places, but no social interaction between nodes is considered.

Other works investigate human mobility in terms of pairwise contact and inter-contact times [4–6]. Recently, underlying mobility patterns have been explored for social-based routing [7, 13, 22]. In particular, Plat et al. propose to use connected dominating sets as message ferries and routing relays [22]. Nevertheless, neither social behavior nor relative importance of mobile nodes are explored, since message ferries are selected based only on neighborhood analysis.

The originality of our work is that we investigate established social-inspired techniques and evaluate the relative importance of mobile nodes in the specific case of data collection. By taking advantage of inherent social cyclicity, we do not need to enforce mobility to help the collection system.

7 Summary and outlook

In this paper, we have addressed the design of system support for robust data collection in wireless networks that face problems as sparse connectivity, high degree of mobility, and unreliable links. We have focused on the case of a data collection system where the number of collectors is much larger than the number of producers. To solve this problem, we have proposed a two-tiered approach where a subset of the producers are promoted to the rank of delegates, which are responsible for helping collectors gather data from the network. By relying on the social behavior of nodes, we moved beyond the current state-of-the-art that introduces particular entities such as data mules or message ferries. To decide which producers to promote, we have investigated several strategies based on the social interactions producers have among them. In building our system, we observe that much can be extracted from the inherent mobility of the nodes and that our prediction strategy is effective when used for delegate selection. Among the many results using existing real mobility traces, we were very surprised to note that local knowledge of the network is more than enough to achieve high collection ratios, with values that are close to those obtained with full knowledge of the topology. As part of ongoing work, we are applying the same analysis to other mobility traces and are working on trajectory design to decide the order in which delegates should be visited by collectors.

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